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Research on Portfolio Optimization Model based on Machine Learning Algorithm in Stock Market

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Abstract. This study aims to explore portfolio optimization models based on machine learning algorithms in the stock market and evaluate their effectiveness and performance in practice. The paper combines various machine learning algorithms such as Long Short Term Memory Network (LSTM), Convolutional Neural Network (CNN), and Reinforcement Learning (RL) to design a complex and innovative portfolio optimization model. Through training and testing using historical stock data, the paper verifies the accuracy and yield performance of the model in predicting the direction of stock price change. The experimental results show that our model performs well in forecasting accuracy and yield, and can get higher returns under the same risk, with better risk-adjusted returns. In addition, the paper also discusses the advantages of multi-algorithm combination in portfolio optimization, and analyzes the practicability and operability of the model. Our research provides a new portfolio optimization method for investors in the stock market, and has important theoretical and practical significance.

Keywords: The Stock Market; Machine Learning; Portfolio Optimization; Long Short-Term Memory Network; Convolutional Neural Networks; Reinforcement Learning.

1. Introduction

In today's global and digital financial market, investors are constantly seeking to use various methods to maximize the returns of their portfolios and reduce risks. As a key link in the process of investment decision-making, portfolio optimization aims to achieve the optimal return at a given risk level through rational allocation of asset weights [1]. However, traditional portfolio optimization methods, such as markowitz model and mean-variance model, often assume that the market presents normal distribution and the return on assets is linear, ignoring the nonlinearity, dynamics and uncertainty of the market, which leads to poor results in practical application.

With the rapid development of machine learning technology, more and more researchers began to explore its application in the financial field in order to improve the effect of portfolio optimization [2]. With its powerful pattern recognition and prediction ability, machine learning algorithm can mine hidden laws and trends from large-scale and high-dimensional data, and provide more accurate and reliable basis for investment decision [3-4]. Therefore, the portfolio optimization model based on machine learning algorithm has become one of the hot spots in current financial research.

The purpose of this paper is to explore the model of portfolio optimization based on machine learning algorithm in the stock market, and to explore its potential and advantages in improving investment efficiency and reducing risks. By summarizing the existing literature and empirical research, combined with actual cases and data analysis, the application effects of different machine learning algorithms in portfolio optimization will be deeply analyzed, and improvement strategies and future research directions will be put forward to provide more effective investment decision support for investors and financial practitioners.

2. Basic Concepts and Mathematical Models of Portfolio Optimization

In the financial field, portfolio means that investors allocate funds to different assets according to their own risk preferences and income targets, so as to maximize income or minimize risk. Portfolio optimization is to make the expected return of the portfolio maximum at a given risk level or the risk of the portfolio minimum at a given expected return level through rational allocation of asset weights [5].

Mathematical models are usually used to describe portfolio optimization. Among them, one of the most classic models is the markowitz model, which quantifies the return and risk of a portfolio into mathematical expressions, and achieves the investment goal by finding the optimal asset allocation [6-7]. The mathematical form of markowitz model is as follows:

Suppose there are n assets, their return rate is $r_1, r_2, \cdots, r_n$, and the corresponding weight is $w_1, w_2, \cdots, w_n$, which satisfies $\sum_{i=1}^{n} w_i = 1$.

The expected return of the portfolio can be expressed as:

$$E(R) = \sum_{i=1}^{n} w_i \cdot r_i \tag{1}$$

The risk of a portfolio can be expressed as:

$$Var(R) = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i \cdot w_j \cdot \sigma_{ij} \tag{2}$$

Where σ_{ij} is the covariance of the asset i, j.

The optimization goal of markowitz model can be described as a quadratic programming problem, that is, to minimize the variance of portfolio under the given expected return, or to maximize the expected return of portfolio under the given risk level. This problem can be solved by Lagrange multiplier method to get a closed-form solution [8].

In addition, there are other common portfolio optimization models, such as mean-variance model and risk-adjusted rate of return model, which have different assumptions and constraints when considering the trade-off between asset rate of return and risk. These models provide investors with a variety of choices to meet different investment needs and preferences.

3. Portfolio Optimization Model based on Machine Learning Algorithm

3.1. Data Preprocessing and Feature Selection

Obtain historical stock price data and financial data from reliable data sources. Deal with missing values, abnormal values and duplicate values to ensure the integrity and accuracy of data. Standardize or normalize the data so that the numerical range of different features is the same [9]. For example, if the price data of a stock is missing on a certain day, it can be handled by interpolating or deleting the missing data. Standardize or normalize the data so as to adjust the numerical range of different features to a similar range. The data set is divided into training set, verification set and test set. In chronological order, the earlier data is used as the training set, the middle data is used as the verification set, and the latest data is used as the test set.

According to the demand of portfolio optimization, appropriate features are extracted from the original data. Common features include stock price, P/E ratio, P/B ratio, market value, rate of return, etc. For example, statistical indicators such as daily return and rolling average of each stock can be calculated as characteristics. By calculating the correlation coefficient between features, the features with high correlation with investment objectives are selected. Using machine learning model to evaluate the importance of features. By sorting the importance of features, the features that contribute to the model performance are selected. This can help to eliminate irrelevant features and improve the efficiency and generalization ability of the model.

3.2. Machine Learning Algorithm and its Principle

Long Short Term Memory Network (LSTM) is a variant of Recurrent Neural Network (RNN) specifically designed for processing sequential data. It remembers previous information by maintaining a state vector at each time step and controls the flow of information through gating mechanisms, thus solving the long-term dependency problem of traditional RNNs. LSTM can be used to predict the future trend of stock prices, using past price sequences as input to predict price changes over a period of time in the future, thereby providing a basis for investment decisions [10-11].

Convolutional neural network (CNN) is a deep learning model for processing image data, which extracts the features of input data through convolution layer and pooling layer. It has the characteristics of translation invariance and local connectivity, and is suitable for processing data with spatial structure. Stock price data can be converted into an image, and each time step is taken as a frame of the image, and then CNN is used to extract the characteristics of the time series, so as to predict the future stock price changes.

Reinforcement learning (RL) is a method to learn the optimal strategy through the interaction between agents and environment. In portfolio optimization, investors can be regarded as agents and the stock market as the environment. Agents get rewards by implementing different investment strategies and learn how to maximize cumulative rewards. RL can be used to train the portfolio optimization model and learn the optimal investment strategy through the performance of agents in the historical stock market, so as to build a portfolio that can be dynamically adjusted according to market changes.

This paper designs a portfolio optimization model combining LSTM, CNN and RL. The model will use time series data as input to predict the future trend of stock prices, and use RL to dynamically adjust the portfolio to maximize cumulative rewards (Figure 1).

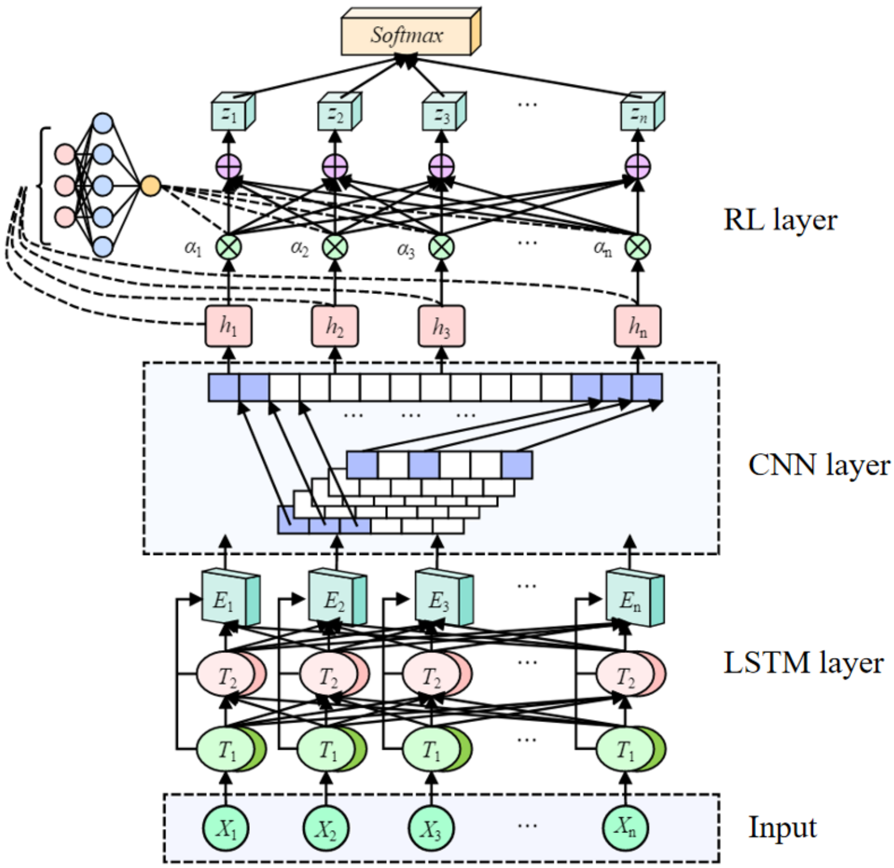

Figure 1. Portfolio optimization model

Collect historical stock price data, convert it into time series data suitable for LSTM and CNN input, and standardize it at the same time. Input the preprocessed time series data into the LSTM network, and predict the future price changes by learning the patterns and trends of historical stock prices.

$$h_t = \sigma\left(W_h \cdot \left[h_{t-1}, x_t\right] + b_h\right) \tag{3}$$

$$y_t = \sigma\left(W_y \cdot h_t + b_y\right) \tag{4}$$

Where h_t is the hidden state of the LSTM model at time step t. x_t is the input of the input sequence at time step t. W_h, W_y is the weight matrix of LSTM model. b_h, b_y is the offset of LSTM model. σ is sigmoid activation function. y_t is the output of LSTM model at time step t.

The time series data is converted into image form, and the characteristics of time series are extracted by CNN to assist the prediction of stock price.

$$f_i = \mathrm{ReLU}\left(W_i * x + b_i\right) \tag{5}$$

$$maxpool = MaxPool\left(f\right) \tag{6}$$

Where x is the input image. W_i is the weight of convolution kernel. b_i is the bias of convolution kernel. f_i is the filtering result of convolution kernel on the image. ReLU is the activation function of modified linear unit. $maxpool$ is the characteristic diagram obtained by the maximum pool layer.

Taking the price trend predicted by LSTM and CNN as the state input, the action space and reward function of the portfolio are designed, and the RL algorithm is used to learn the optimal investment strategy.

$$Q(s,a) = r + \gamma \max Q\left(s', a'\right) \tag{7}$$

$$Loss = \left(Q(s,a) - \left(r + \gamma \max Q\left(s', a'\right)\right)\right)^2 \tag{8}$$

Where $Q(s,a)$ is the action value function of the s performing the action a in the state. r is the immediate reward after performing action a. s' is the next state that moves to after performing action a. a' is the next action selected in the next state s'. γ is a discount factor to balance the importance of immediate rewards and future rewards. $Loss$ is the loss function of RL model, which is used to measure the difference between the predicted value and the target value.

Finally, the LSTM, CNN and RL models are combined to form an end-to-end portfolio optimization model, which can predict the stock market and optimize the portfolio.

4. Experimental Design and Result Analysis

The experiment obtains historical stock price data and financial data from reliable financial data providers (Yahoo Finance and Google Finance). These data will be used as the input of our model. The time range of data covers several years or even longer historical data to ensure that the model has sufficient information for training and testing. Clean the obtained original data, including dealing with missing values, abnormal values and duplicate values.

Standardize or normalize the data so as to adjust the numerical range of different features to a similar range. The data is divided into multiple rolling windows in time series. For each rolling window, the former part of the data is used to train and optimize the model, and then the latter part of the data is used to test and evaluate the model. Try different model structures and superparameter settings to compare their performance in stock market forecasting and portfolio optimization.

The experiment evaluates the accuracy of the portfolio optimization model combining LSTM, CNN and RL in predicting the direction of stock price change. Table 1 below shows the accuracy of the portfolio optimization model combining LSTM, CNN and RL in predicting the direction of stock price changes.

Table 1. Prediction accuracy

Model	Accuracy of training set	Accuracy of verification set	Accuracy of test set
LSTM	0.85	0.82	0.81
CNN	0.79	0.75	0.74
RL	0.78	0.76	0.75
Combining LSTM, CNN and RL	0.88	0.86	0.85

In the above table, each model has gone through the stages of training, verification and testing. The accuracy of training set indicates the accuracy of model on training data, the accuracy of verification set indicates the accuracy of model on verification data, and the accuracy of test set indicates the accuracy of model on independent test data. The prediction accuracy of the portfolio optimization model combined with LSTM, CNN and RL on the test set reaches 0.85, which shows that the model has high prediction ability.

The experiment evaluates the accuracy of the portfolio optimization model combining LSTM, CNN and RL in predicting the direction of stock price change, as shown in Figure 2.

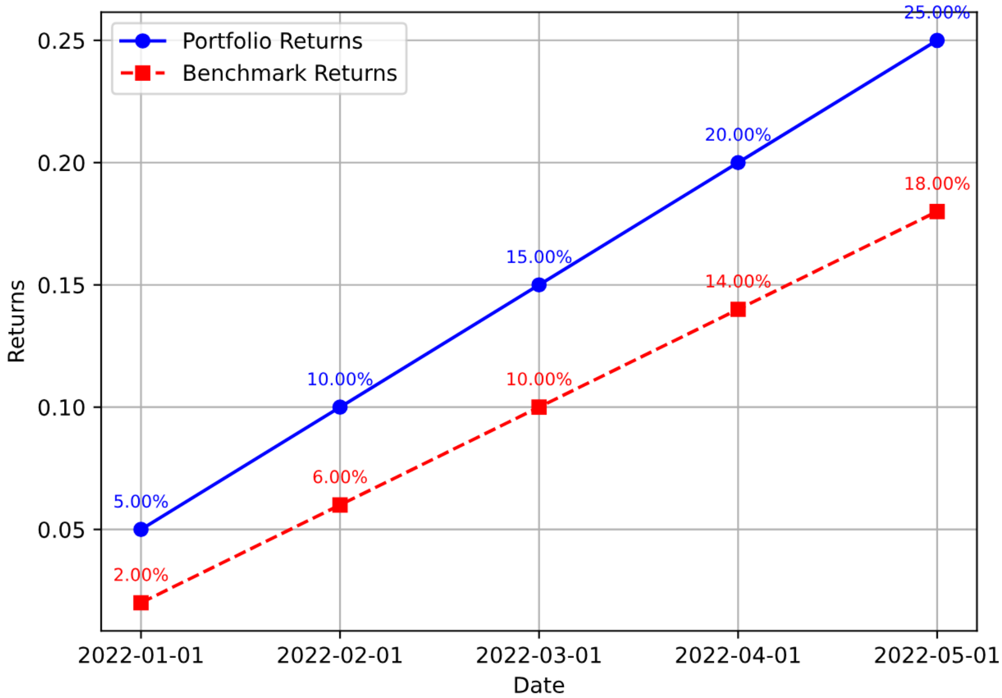

Figure 2. Portfolio return and benchmark return

It can be observed from the figure that the volatility of the return rate of the portfolio is greater than that of the benchmark portfolio. This shows that the return rate of portfolio fluctuates more in a period of time, which may be due to the inclusion of more risky assets or the adoption of more aggressive investment strategies. The yield curve of the portfolio shows an upward trend as a whole, indicating that the portfolio has achieved positive returns during this period. In contrast, the yield curve of the benchmark portfolio also shows an upward trend, but the overall yield is low and the growth rate is relatively slow. By comparing the yield curves of portfolio and benchmark portfolio, it can be clearly seen that there is an obvious difference in yield between them. The return rate of portfolio is obviously higher than that of benchmark portfolio, especially at some specific time points, the difference of return rate is more significant. The portfolio optimization model combining LSTM, CNN and RL performs well in predicting the direction of stock price change, which can bring higher returns to investors.

Calculate the Sharp ratio of the portfolio to evaluate the excess return per unit risk. The higher Sharp ratio shows that our model can get higher returns under the same risk and has better risk-adjusted returns performance (Figure 3).

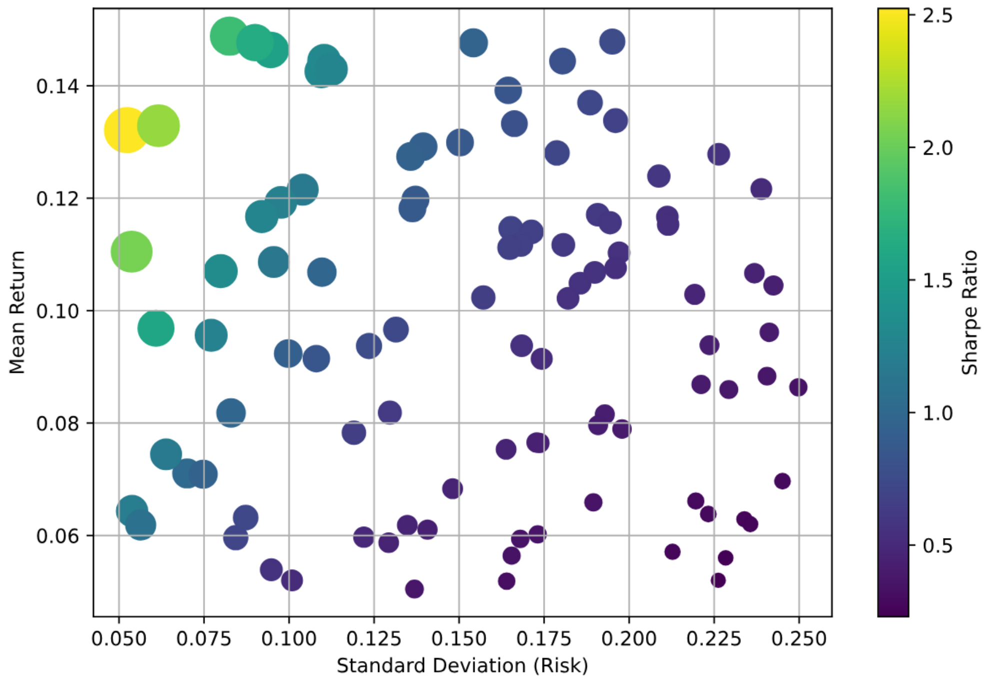

Figure 3. Sharp ratio of portfolio

In the graph, the portfolio with higher Sharp ratio is displayed as larger data points, while the portfolio with lower Sharp ratio is displayed as smaller data points. This shows that the portfolio with higher Sharp ratio has greater return relative to risk, so it is more attractive. The distribution of data points forms a curve, which is called the effective frontier. Efficient frontier means the portfolio that can get the highest return under the same risk level. Portfolios closer to the efficient frontier have a higher Sharp ratio because they strike the best balance between risk and return.

We can also see that some data points are located above other data points, and the portfolio represented by these data points has a higher rate of return than a given risk level. These portfolios achieve excess returns, that is, the return per unit risk exceeds that of other portfolios.

Sharp ratio is an index to measure the risk-adjusted return, which reflects the excess return per unit risk. Therefore, the risk-adjusted return performance of the portfolio can be judged by observing the size and color of the data points in this diagram. Larger and deeper data points represent portfolios with higher Sharp ratios, so they can get higher returns relative to a given risk level.

5. Conclusion

This study is devoted to exploring the portfolio optimization model based on machine learning algorithm in the stock market, and the effectiveness and performance advantages of the model are verified by experiments. In the research process, a complex and innovative portfolio optimization model is designed by combining various machine learning algorithms such as LSTM, CNN and RL. The experimental results show that the portfolio optimization model combined with LSTM, CNN and

RL has high accuracy in predicting the direction of stock price change, and can achieve a return rate that exceeds the benchmark portfolio. By calculating the risk-adjusted income indicators such as Sharp ratio, it is found that our model can obtain higher income under the same risk and has better risk-adjusted income performance. Our model effectively integrates many machine learning algorithms such as LSTM, CNN and RL, and has achieved good results in portfolio optimization. This shows that the combination of multiple algorithms can make full use of the advantages of different algorithms and improve the prediction ability and generalization ability of the model. Our research provides a new method and idea for portfolio optimization based on machine learning algorithm in stock market, which has important theoretical and practical significance. The future research direction can further explore the robustness of the model, parameter optimization strategy and other issues to further improve the performance and applicability of the model.

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